

Assimilation of Coastal Radar Surface Current Measurements in Shelf Circulation Models

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LONG-TERM GOALS

We aim to assess the amount of information the surface currents can provide about the state of the ocean at depth, to find the best approach for the extraction of this information, and to assess the necessary ingredients that the dynamical models and assimilation schemes must retain for successful use of the surface data in practical analysis and prediction systems.

OBJECTIVES

First, we aim to assess the possible retrieval of information about the ocean state at depth from surface data in a simple linear model. We will perform simulation experiments in which we will apply an optimal data assimilation scheme to our simple model in order to obtain an inverse solution that is an optimal fit to the model and to the data. Our first model is sufficiently simple that significant progress can be made through the use of analytical tools alone. The focus is on quantifying the information content of the surface data, and how the data, data errors, and other assumed error statistics influence the inverse solution. Second, we aim to compare the above retrieval of depth information with retrieval using suboptimal assimilation schemes, again using a simple model to allow analytic progress and direct comparison. Third, we aim to use these comparisons as guidance in the selection of computationally efficient assimilation schemes for use with fuller dynamical models.

APPROACH

To address the first objective, we use a forward model that has been used in previous idealized studies of the coastal ocean (e.g., Allen, 1973) and assimilate simulated surface data using a variational assimilation scheme that provides a least-squares best fit to the model and to the data. Analytic solutions are obtained in different frequency limits, illustrating explicitly the dependence of the inverse solution on the assumed error statistics, or weights. We will begin to address the second and third objectives by applying different suboptimal assimilation schemes to the same analytic model. Numerical experiments will be performed with models of intermediate complexity, i.e., more detailed than our complex model but still simple by comparison with general models such as the Princeton Ocean Model (POM). These models, though simple, will be analytically intractable, but with features readily interpretable in terms of our analytical results on the one hand, and detailed models on the other. Different suboptimal assimilation schemes will thus be applied to a suite of models of increasing complexity from our analytical model to fully general nonlinear models. The focus here will be on idealized numerical simulations aimed at quantifying the retrieval of depth information from surface data in the different suboptimal

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schemes.

WORK COMPLETED

We have completed the first of the above objectives. A simple model has been identified that allows analytic progress for both the forward solution and the inverse solution in two limiting cases. The forward model is a linear, stratified, boussinesq, primitive equation model using a simple geometric representation of the near-shore region. Wind forcing is applied through a vanishingly thin surface Ekman layer (Allen, 1973). The inverse model comprises the forward model and a set of adjoint equations, the solution of which minimizes a penalty functional of data and model errors to provide a weighted least squares fit to the forward model and to the data. Strong and weak constraint formulations of the inverse model have been investigated. In the strong constraint formulation the only source of model error is in the open ocean boundary condition; the model dynamics are assumed to be perfect. In the weak there are sources of model error in both the open ocean boundary condition and the model equations themselves.

Analytic expressions for the inverse solutions have been obtained in both the strong and the weak constraint formulations in terms of a sum of representer functions, over the data array. There is a representer function associated with each observation in space and time, so, for example, a scheme for assimilating daily data taken for a month at two different locations would be written in terms of sixty representers. The representer function for a given observation contains information about the impact of assimilating the result of that particular observation into the analysis for a given model and given cost function. The impact of that observation is greatest where the representer takes its maximum. Assimilation of the given observation will result in little improvement at locations where the value of the representer is small.

The inverse solution in this form has provided considerable insight into the influence of the weights used in the penalty functional, and hence into the influence of the assumed model and data error statistics. The representer functions themselves have provided insight into the influence of individual data points, indications of the optimal design of the data array, and allowed for detailed comparison of the strong and the weak constraint formulations. Spectral analysis of the representer matrices have also provided useful comparisons of the strong and the weak formulations.

Twin experiments have been investigated, in which data were sampled from a known ocean state, for example from the solution to the forward model, to assess how well the inverse method can recreate the original ocean state. The dependence of the inverse solution on the data error variance has been shown explicitly. Further, a measure of the total error of the inverse solution from the known ocean state has been used to determine which model weights provide the best inverse solution, and simple statistics of the total error have been computed.

For completeness, we have also investigated alternative forms of the inverse problem in both the strong and the weak constraint formulations. In particular, we have investigated alternative open ocean boundary conditions, motivated by different physical considerations, and investigated alternative ways of representing the model errors in the penalty functional.

RESULTS

We have gained an understanding of how the strong constraint inverse model approach resolves ill-posedness associated with the inclusion of surface data in our dynamical model. The ill-posedness arises firstly because direct insertion of the extra surface data in an already well-posed forward model results in an over-determined system, and secondly because attempts to avoid an over-determined system by discarding the open ocean boundary condition result in a system with a solution that depends unstably on the surface data. The unstable dependence of the solution on the surface data is resolved in the inverse model by constraining the open ocean boundary condition to be small in some sense, and the unique solution to the inverse problem is the best fit to the data and to the open ocean constraint. The analytic form of the inverse solution has provided a clear understanding of how the inverse solution depends on the relative weights given to the data and to the open ocean constraint. Since the open ocean constraint is not physically based, it is not possible to construct meaningful error statistics and therefore the weights must be chosen heuristically. Consideration of the spectral properties of the representer matrix, in particular the decay of the eigenvalues, indicates how such weights may be chosen depending on the required spatial structure of the inverse solution. Consideration of individual terms in the penalty functional, on the other hand, illustrates the compromise between fitting the data more closely and keeping the open ocean values relatively small. Both considerations may be used in the selection of the weights in the absence of other statistical information.

Study of the weak constraint inverse formulation has provided similar insight. In this case, model errors are included and there is an additional weight to choose. Again, analytic forms of the inverse solution reveal explicitly the dependence of the inverse solution on the choice of the model and other weights. Consideration of the spectral properties of the representer matrix illustrate how different choices of model and open ocean weights affect both the spatial structure of the inverse solution and the relative influence of the data on the interior and open ocean parts of the solution. Contour maps of representer functions in the x - z plane, where x is the cross-shore direction and z is depth, are shown in the accompanying figure. Representers are shown for observations at two points in space and for four different choices of weights, including the strong constraint case.

In both the strong and the weak constraint formulations the representer functions indicate that the data has considerable influence on the inverse solution at depth, and hence on the ability to reconstruct a particular ocean field. The availability of analytic solutions to the weak and strong constraint inverse problems allows us to understand the strong constraint solution as a limiting case of the family of weak constraint solutions with different weights.

Consideration of twin experiments provides a direct indication of how well we can reconstruct a known ocean state from data sampled at the surface. In the case that the known state satisfies our forward model exactly, the reconstruction is successful, even when the sampling errors are moderately large. On the other hand, when the known ocean state is far from satisfying our forward model exactly, the reconstruction is less successful, even when the sampling errors are small. The reason comes from the special geometry of the problem and the modal structure in the vertical. Considerations of ensembles of twin experiments have also provided useful insight. In particular, a decomposition of the total squared error of the inverse solution into contributions from the array resolution and from the inversion matrix reveal how much information is lost by sampling resolution and how instability of the inverse solution arises

when the data errors are considered to be too small.

IMPACT/APPLICATIONS

Our study has begun to answer some of the questions associated with the assimilation of surface current measurements in coastal ocean models. In particular we have investigated the information content of surface data about the ocean at depth, how such information may be retrieved using data assimilation in a dynamical model, and how the inverse solution obtained through the assimilation depends upon assumed model and data error weights. A better understanding of such issues is essential for the correct selection of data assimilation techniques in more complicated models using the real surface current data that is becoming increasingly available from coastal radar measurements.

TRANSITIONS

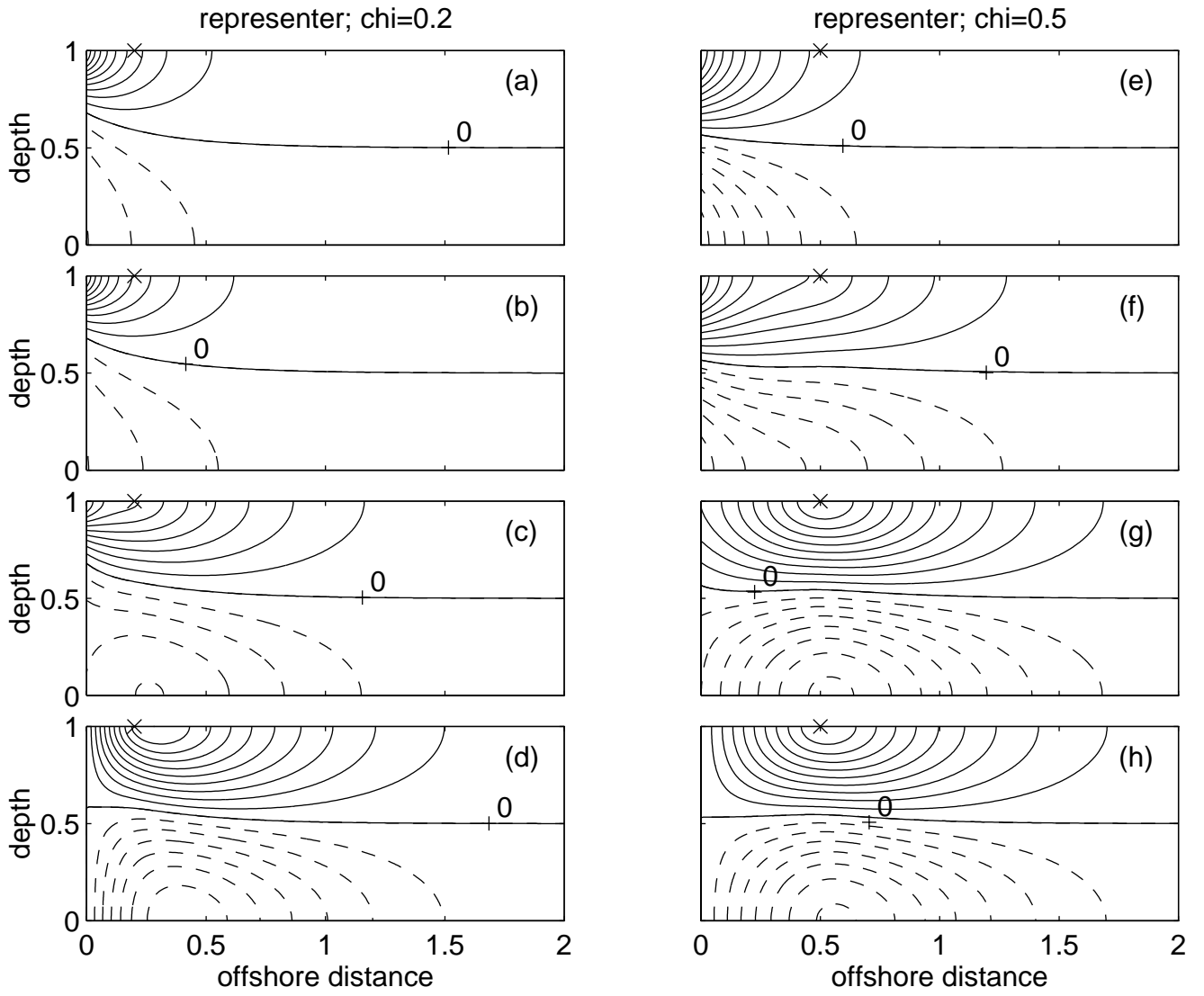
RELATED PROJECTS

“The Prediction of Wind-Driven Coastal Circulation,” a two-year program under the National Oceanographic Partnership Program (NOPP) began last summer. The objective of that two-year project is to produce a practical nowcast system for the ocean off the Oregon coast. This project includes a modeling and a field component. The NOPP team includes Professors Allen and Miller

REFERENCES

J. S. Allen. 1973. Upwelling and coastal jets in a continuously stratified ocean. *Journal of Physical Oceanography*, 3, 245-257.

PUBLICATIONS



Normalized representer functions for surface data located at an offshore distance of $c = 0.2$ (a-d) and $c = 0.5$ (e-h), for different values of model and open ocean error weights, v and w . These maps show the influence of surface data on the pressure anomaly field throughout the model domain. Panels (a,e) depict the strong constraint limit, i.e., v/w approaches infinity; the remainder are for the weak constraint as follows: (b,f) $v/w=0.1$; (c,g) $v/w=0.01$; (d,h) $v/w=0$. Solid lines denote positive values, dashed denote negative, and the contour interval is 0.1 in each case.